

Benchmarking EEG Headset Layouts for Motor Imagery BCIs in the Internet of Sounds

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Abstract—Research in Brain–Computer Interfaces (BCIs) is often developed with high-density laboratory EEG caps, whereas BCI-enabled Internet of Sounds (IoS) applications typically require portable, low-density, and wireless headsets for networked sound interaction. For motor imagery BCIs, electrode layout can strongly affect whether a wearable headset captures task-relevant brain activity, but this aspect remains difficult to compare across commercial devices. In this paper, we present a device-aware topology benchmark for commercial EEG headsets considered as candidate BCI sensing nodes for IoS systems. Starting from a public 64-channel dataset of left- vs. right-hand motor imagery as the reference recording, we model 32 commercial headset layouts as electrode masks and compare them across five classification pipelines within the MOABB framework. We report systematic differences in decoding performance across commercial electrode layouts, including layouts with similar matched channel counts but different sensorimotor coverage. This analysis supports early-stage headset screening and trade-offs between portability, cortical coverage, and control reliability for networked musical and sound-based BCI applications.

Index Terms—Internet of Sounds, Brain–Computer Interface, Motor Imagery, Wearable EEG

I. INTRODUCTION

The Internet of Sounds (IoS) extends sound and music computing toward ecosystems of networked Sound Things, namely devices capable of sensing, acquiring, processing, actuating, and exchanging data for sound-related communication [1]. In this scenario, Brain–Computer Interfaces (BCIs) can be understood as neurophysiological sensing nodes within networked interactive systems [2]. BCIs translate brain activity into control signals for external devices, enabling communication and interaction without requiring explicit muscle activity [3], [4]. Among non-invasive BCI approaches, electroencephalography (EEG) remains widely used due to its portability, temporal resolution, and relatively low cost. Recent work increasingly targets deployment beyond laboratory settings, where setup time and comfort become central constraints [5].

BCI-enabled IoS applications may include networked musical interfaces, interactive sound installations, adaptive sonic environments, and therapeutic or accessibility-oriented systems [6]. Within this broader space, Brain–Computer Musical Interfaces (BCMIs) [7] map brain activity to music-related control signals for performance, interaction, and therapeutic engagement [8]. BCMI research spans multiple EEG paradigms and interaction strategies, reflecting an evolving

landscape of music-oriented neurotechnology beyond any single control approach [9], [10]. In this work, we focus on motor imagery (MI), a well-established active BCI paradigm grounded in evidence that imagined and executed movements engage overlapping brain networks [11].

Motor imagery provides a useful case study for topology-aware BCI evaluation because it is an intention-driven paradigm in which users deliberately modulate sensorimotor rhythms, rather than relying on stimulus-evoked responses. These modulations are typically observed in the sensorimotor μ rhythm, which occupies the alpha-frequency range (~ 8 – 13 Hz), and in the β band (~ 13 – 30 Hz) during imagined movements. Crucially, their discriminative value depends on their spatial distribution across scalp sites, with informative patterns usually strongest over central sensorimotor areas [12], [13]. For example, left- vs. right-hand imagery produces lateralized topographies that can be captured reliably only when electrodes sample these regions; therefore, electrode placement can matter as much as band selection.

Effective MI control also depends on inter-user variability [14], training, fatigue [15], feedback design, and signal quality [16]. Laboratory MI studies typically optimize these conditions with high-density caps and controlled recordings, allowing dense scalp coverage and post hoc channel selection. By contrast, BCI-enabled IoS applications foreground the need for portable sensing devices that can be integrated into networked sound-interaction pipelines [17]. Wearable EEG headsets therefore trade controlled acquisition for portability, comfort, affordability, wireless operation, and rapid setup. These devices use fixed low-density layouts, often designed around usability rather than MI-specific cortical coverage. This shift can affect not only decoding accuracy, but also performance consistency across users, directly impacting the reliability of MI as an interaction modality.

This motivates a concrete research question: *how do MI decoding performance and variability change when moving from laboratory caps to commercial wearable headsets with low-density layouts?*

This paper addresses this question with a device-aware topology benchmark focused on electrode-layout constraints. We selected 32 commercial wearable EEG headsets whose profiles include IoS-relevant integration features such as portability, wireless connectivity, real-time data access, SDK/API

availability, and battery-powered operation. Using a public 64-channel left- vs. right-hand MI dataset [18], we model these devices as virtual headsets, namely electrode masks matching real headset layouts, and perform EEG channel reduction within the MOABB (Mother of All BCI Benchmarks) framework [19]. We evaluate five reference pipelines under within-session and cross-subject protocols, and report performance and variability across the commercial layouts. The benchmark is intended as a controlled analysis of topology and channel count, rather than as a complete ranking of physical EEG products. Accordingly, the proposed analysis provides an interpretable baseline for early-stage screening of wearable EEG headsets as BCI sensing nodes in networked musical and sound-based IoS applications.

The main contributions of this work are the following:

- a Python-based headset-profile module covering 32 commercial wearable EEG headsets, encoding electrode layouts and deployment-relevant device attributes and designed for reuse across different datasets and BCI paradigms (Section III);
- a topology-focused benchmark implemented in MOABB, comparing five reference MI classification pipelines under two evaluation protocols (Section IV);
- quantitative evidence to support trade-offs between portability, cortical coverage, and MI decoding reliability (Sections V and VI).

II. BACKGROUND

BCI-enabled IoS systems sit at the intersection of networked sound interaction, wearable sensing, and real-time control. Recent work has begun to explore this direction explicitly: BCHJam, for example, integrates BCMI, smart musical instruments, mixed reality headsets, performers, and audience members into a performance ecosystem, with BCI-derived control streams communicated through a local network [17]. More broadly, Internet-of-Things research frames brain signals as a channel for interacting with connected devices [2], [20], while mobile EEG-BCI prototypes emphasize the importance of interoperability, portability, usability, and reliability for deployment beyond the laboratory [21]. In music and accessibility contexts, low-density, dry, wireless EEG systems have also been used for brain-computer music interaction, showing the practical relevance of portable acquisition even when the paradigm differs from MI [22]. These works motivate considering wearable EEG headsets as candidate sensing nodes whose usefulness depends on both integration constraints and access to task-relevant cortical activity.

For BCIs based on motor imagery, this access is strongly shaped by electrode topology, because discriminative activity is spatially concentrated over sensorimotor areas. Left- vs. right-hand imagery typically yields lateralized activity over central sensorimotor areas, motivating region-of-interest recording strategies that aim to reduce setup time and improve comfort while preserving discriminative information. Throughout this paper, we adopt the standard 10–10 electrode-position nomenclature, where letters denote scalp regions, odd and

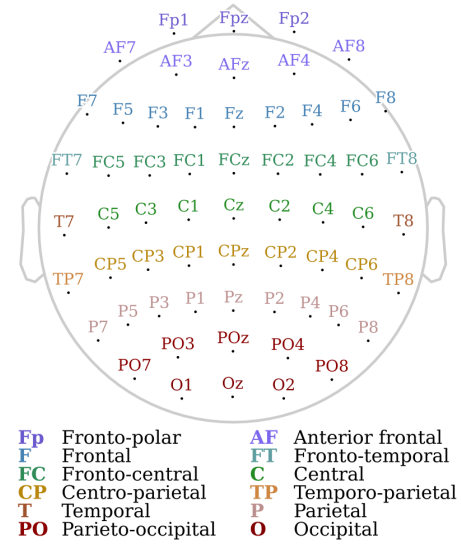


Fig. 1. Electrode layout in the reference dataset, with standard channel labels.

even indices denote left and right hemisphere positions, and *z* denotes the midline (Figure 1). Within this convention, source-localization and channel-selection studies consistently identify fronto-central (FC), central (C), and centro-parietal (CP) sites around the sensorimotor strip as particularly relevant for MI decoding [23]. This provides a knowledge-based reference for assessing whether a commercial headset layout plausibly samples MI-relevant scalp regions.

A substantial body of work studies EEG channel selection and channel reduction for MI [24], [25]. These methods show that competitive decoding can often be achieved with reduced montages, but they typically search for optimal channel subsets within a given recording montage. Such subsets do not necessarily correspond to the fixed, uneven electrode layouts available in commercial wearable headsets. Similarly, recent data-driven approaches can improve channel reduction across datasets [26], but they do not directly compare purchasable headset families as deployment-constrained sensing nodes.

In parallel, reviews of EEG equipment and wearable MI technologies emphasize that form factor, setup speed, channel count, fixed electrode placement, and comfort shape what can be realistically deployed outside the laboratory [16], [27], [28]. However, these works generally discuss hardware characteristics or wearable design constraints without quantifying how much MI decoding performance changes when dense laboratory recordings are constrained to commercial headset topologies. Taken together, this leaves a practical gap for BCI-enabled IoS design: there is limited reproducible evidence that links wearable headset profiles with a controlled evaluation of electrode layout under shared pipelines and evaluation protocols.

III. HEADSET COLLECTION

Wearable EEG devices impose deployment constraints that can be as limiting as decoding accuracy outside the laboratory,

TABLE I

LIST OF 32 COMMERCIAL WEARABLE EEG HEADSETS FROM 13 COMPANIES. ABBREVIATIONS: ACCEL. = ACCELEROMETER; EXG = AUXILIARY ELECTROPHYSIOLOGICAL CHANNELS; IMU = INERTIAL MEASUREMENT UNIT; LSL = LAB STREAMING LAYER; N.S. = NOT SPECIFIED. IN THE RAW/API COLUMN, F = FREE/OPEN ACCESS, P = PAID LICENSE REQUIRED, M = MIXED ACCESS MODEL, AND U = UNCLEAR OR NOT PUBLICLY VERIFIED.

Company	Product	Form	Mask Ch.	Electrodes	Extra sensors	Connectivity	Raw/API	Battery (h)
Advanced Brain Monitoring [29]	B-Alert X24	Helmet	20	Wet	Accel., opt. ExG	BT/USB	P: SDK/raw	>12
	B-Alert X10	Helmet	9	Wet	Accel., opt. ExG	BT/USB	P: SDK/raw	>12
Bitbrain [30]	Diadem	Helmet	12	Dry	9-axis IMU	BT	F: SDK/LSL/storage	6–12
	Hero	Helmet	9	Dry	9-axis IMU	BT	F: SDK/LSL/storage	≤6
	Air	Helmet	8	Dry	9-axis IMU	BT	F: SDK/LSL/storage	6–12
	Ikron	Headband	5	Dry textile	9-axis IMU	BT	F: SDK/LSL/storage	6–12
BrainBit [31]	DragonEEG	Cap	21	Dry/Wet	3×ExG	BT adapter	F: SDK/storage	n.s.
	Headband Pro	Headband	8	Dry	n.s.	BT	M: App/SDK	n.s.
	Headband	Headband	4	Dry	n.s.	BLE	F: SDK/raw	6–12
	Headphones	Headphones	3	Dry	Microphone	BT	F: SDK/raw	n.s.
CGX [32]	Quick 32R	Helmet	29	Dry	Accel., 2×ExG	BLE	U: Streaming API	6–12
	Quick 20R	Helmet	19	Dry	Accel., 2×ExG	BLE	U: Streaming API	6–12
Emotiv [33]	Flex 2	Cap	28	Saline/Gel	9-axis IMU	BT 5.2	P: App/PRO raw	≤6
	EPOC X	Helmet	14	Saline	9-axis IMU	BLE/USB	P: App/PRO raw	6–12
	Insight	Helmet	5	Semi-dry	9-axis IMU	BLE/2.4 GHz	P: App/PRO raw	>12
	MN8	Headphones	2	Dry	Mic., 6-axis IMU	BLE	U: App/raw	≤6
g.Tec [34]	Unicorn Hybrid	Cap	8	Dry/Gel	6-axis IMU	USB/BT	F: API/LSL/UDP	≤6
InteraXon [35]	Muse 2	Helmet	2	Dry	PPG, IMU	BT	M: App/SDK	≤6
	Muse S Athena	Headband	2	Dry	PPG, fNIRS, IMU	BT	M: App/SDK	≤6
MindRove [36]	Vision	Headband	8	Semi-dry	6-axis IMU	WiFi Direct	F: SDK/LSL/raw	≤6
	Arc	Helmet	6	Semi-dry	6-axis IMU	WiFi Direct	F: SDK/LSL/raw	≤6
	Lucid	Headband	6	Semi-dry	6-axis IMU	WiFi Direct	F: SDK/LSL/raw	≤6
	Bright	Headband	4	Semi-dry	6-axis IMU	WiFi Direct	F: SDK/LSL/raw	≤6
Neeuro [37]	SenzeBand	Headband	4	Dry	PPG, SpO ₂ , IMU	BT 5.0	U: 3rd-party apps	≤6
Neurocity [38]	Crown	Helmet	8	Dry	Accel., haptics	BT/BLE/WiFi/USB	M: App/SDK	≤6
NeuroSky [39]	MindWave 2	Helmet	1	Dry	n.s.	BT/BLE	M: App/SDK	6–12
OpenBCI [40]	Ultracortex 16	Helmet	16	Dry	Board-dep. IMU	Board-dep.	F: Open SDK	n.s.
	Ultracortex 8	Helmet	8	Dry	Board-dep. IMU	Board-dep.	F: Open SDK	n.s.
Wearable Sensing [41]	DSI 24	Helmet	19	Dry	Aux. ExG, accel.	BT	F: API/LSL/raw	>12
	DSI 7	Helmet	7	Dry	Aux. ExG, accel.	BT	F: API/LSL/raw	>12
	DSI VR300	Helmet	7	Dry	n.s.	BT	F: API/LSL/raw	6–12
	DSI VRVEP	Helmet	7	Dry	n.s.	BT	F: API/LSL/raw	6–12

including setup time, comfort, and mechanical stability [42], [43]. In BCI-enabled IoS systems, these constraints become part of the sensing-node design problem: a headset should not only provide a suitable electrode layout, but also a connectivity model, data-access pathway, and autonomy compatible with networked sound-interaction scenarios. Wearable systems also differ in electrode technology, such as dry, semi-dry, wet gel, or wet saline sensors, which can affect preparation time, contact quality, and signal reliability [44]. Since these factors depend on the physical device and usage conditions, the decoding benchmark presented in this paper focuses on electrode topology, while the headset collection reports device-level attributes relevant to deployment.

Candidate devices were identified by cross-referencing recent surveys of wearable and wireless EEG systems [45], [46], an MI-oriented review of wearable technologies [16], and manufacturer documentation. Inclusion required a wearable EEG system with sufficient technical information for IoS-relevant assessment and a fixed electrode layout; fully modular systems were excluded to avoid an unconstrained combinatorial design space. Devices not designed for MI, including sparse layouts with limited central coverage, were deliberately retained to represent the broader wearable EEG ecosystem and provide lower-bound references. Poor decoding in these cases is therefore interpreted as task–layout incompatibility for left- vs. right-hand MI, rather than as a general evidence of

hardware inefficiency for BCI applications.

The collection was implemented as a Python module in which each headset is represented by a structured profile containing the electrode layout and deployment-relevant metadata, including form factor, sampling rate, reference scheme, sensor type, connectivity, battery life, raw-data access, SDK/API availability, additional sensors, and product documentation. The Python module, including complete channel lists and metadata, is provided in the companion repository [47].

Table I reports a compact subset of these attributes. For reporting purposes, we group devices by form factor, used here as a coarse descriptor of deployment conditions.

- **Cap:** distributed coverage through a standard EEG cap;
- **Helmet:** rigid or semi-rigid frame;
- **Headband:** elastic or textile band with sparse positions;
- **Headphones:** audio headphones with electrodes.

To ensure consistent comparability across headsets and the reference dataset, channel labels were normalized to a common naming convention by mapping legacy labels (T3/T4/T5/T6) to modern equivalents (T7/T8/P7/P8). Channels that could not be mapped to the reference montage were omitted in the masking process, and the resulting matched channel count was used in all benchmark runs. In particular, *Emotiv Flex 2* has four mismatches (FT9, FT10, TP9, TP10), and both *Muse 2* and *Muse S Athena* omit TP9 and TP10, as they share the same electrode topology despite different form factors. Figure 2

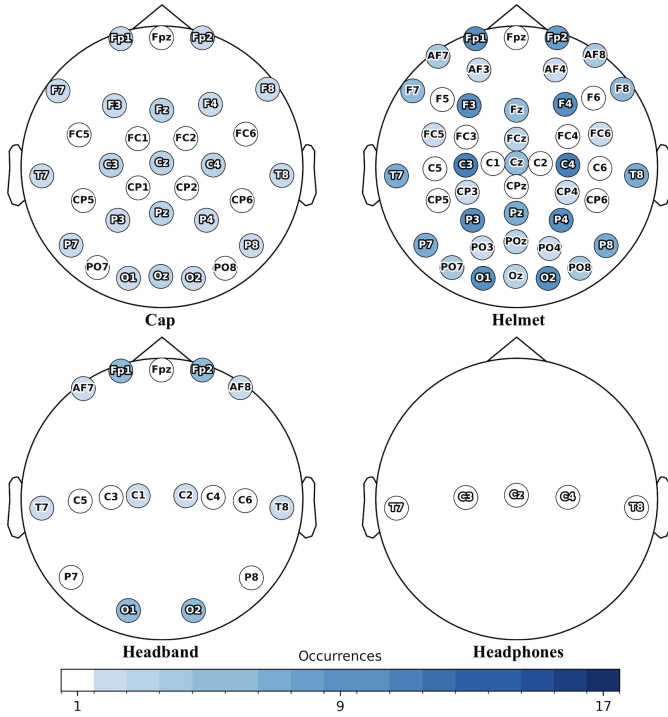


Fig. 2. Electrode-occurrence maps for the four wearable form factors in the headset collection. Marker intensity indicates how often each electrode position appears across the layout masks.

visualizes electrode-occurrence maps for each form factor after channel-name normalization and matching to the reference dataset.

IV. BENCHMARK DESIGN AND METHODS

The benchmark is implemented in Python using the MOABB library [19], which standardizes dataset access, EEG processing, pipeline evaluation, and scoring through MNE-compatible data structures [48]. MOABB is specifically designed to support reproducible comparisons across BCI algorithms, paradigms, and datasets¹. In this study, it is used to keep preprocessing, pipeline families, and evaluation protocols fixed while varying the electrode mask.

Figure 3 summarizes the adopted workflow. Starting from a public 64-channel MI dataset (Subsection IV-A), each commercial device is modeled as an electrode mask (Section III) and passed to the MOABB motor imagery paradigm through the `channels` argument. The paradigm applies consistent preprocessing and yields MNE-compatible epochs and labels. We then evaluate a fixed set of five reference pipelines (Subsection IV-B) under two complementary protocols (Subsection IV-C). The first is a within-session k-fold cross-validation protocol, modeling a user-calibrated setting in which the decoder is trained using subject-specific calibration data; we refer to it as the *Performer-specific* protocol. The second is a cross-subject leave-one-subject-out (LOSO) protocol, modeling plug-and-play use with unseen users in public-facing

or shared sound-interaction contexts; we refer to it as the *Public-facing* protocol. Results are reported in Section V and aggregated for each electrode mask and pipeline as $\text{mean} \pm \text{std}$ across subjects.

A. Dataset

MOABB provides several MI datasets. This study uses Cho2017 as the reference dataset because it is public, well documented, and provides a 64-channel EEG montage arranged according to the international 10–10 system [18]. This makes it suitable for systematic channel reduction: many commercial headsets rely on 10–20 or 10–10-derived electrode positions, allowing their layouts to be approximated as masks over the original montage.

Cho2017 contains recordings from 52 healthy participants (33 male, 19 female; mean age 24.8 ± 3.86 years; 50 right-handed, 2 ambidextrous), acquired with a Biosemi ActiveTwo system and recorded using BCI2000 at 512 Hz. The core task is a two-class MI paradigm (left vs. right hand) with ~ 100 trials per class per subject, collected in a single session, enabling consistent estimation under both within-session and cross-subject protocols. During acquisition, electromyography (EMG) was recorded alongside EEG to help identify trials contaminated by overt movement. The dataset also provides auxiliary recordings, including resting-state and common-artifact, as well as electrode coordinates, quality-related annotations, and participant questionnaires.

A distinctive aspect of Cho2017 is that participants were trained on a brief, structured finger-to-thumb opposition sequence, from index to little finger within a 3 s window, and were instructed to perform MI in a kinaesthetic rather than purely visual mode. This design choice is relevant for decoding because kinaesthetic imagery has been reported to improve MI classification [49]. Participants also received performance feedback during the experiment, which may have supported task engagement and consistency across trials.

B. Classification Pipelines

To isolate the effect of electrode layout, all headset masks are evaluated under the same MOABB motor imagery paradigm. We apply the standard MOABB 8–32 Hz band-pass filtering and extract cue-locked epochs over the 0–3 s task interval defined in the dataset. Within the MOABB paradigm, the only headset-specific parameter is the `channels` argument, which determines which sensors are retained from the original 64-channel montage. For decoding, we adopt five MOABB reference pipelines [50]. These pipelines are computationally lightweight, belong to established families in EEG–BCI classification [51], and remain widely used in motor imagery and wearable-EEG studies [16], [28]. For the dataset considered here, MOABB’s publicly reported within-session results also place them among the stronger baselines².

The selected pipelines span two complementary EEG representations: supervised spatial filtering through common spatial

¹<https://moabb.neurotechx.com/docs/index.html> (accessed Jun 10, 2026)

²https://moabb.neurotechx.com/docs/paper_results.html (accessed Jun 10, 2026)

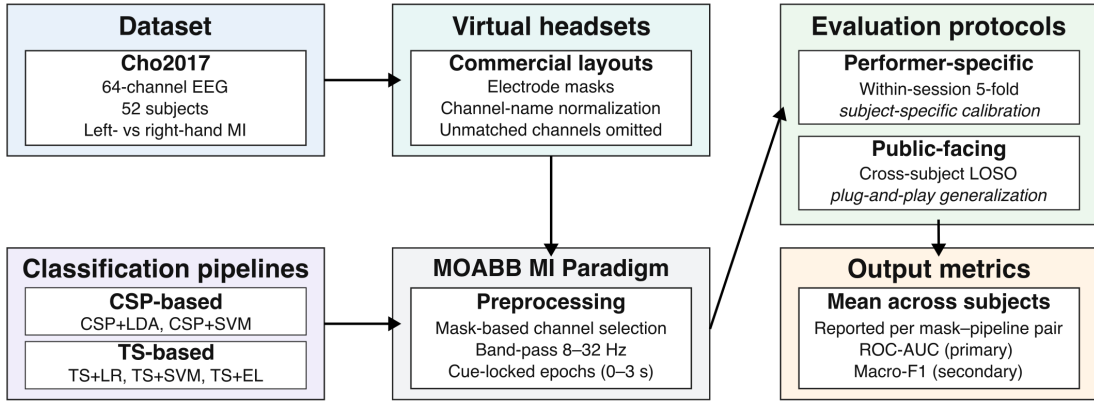


Fig. 3. Device-aware MOABB workflow. Commercial headset layouts are modeled as electrode masks, applied to Cho2017, and evaluated with five pipelines under performer-specific within-session and public-facing cross-subject protocols; results are reported per mask-pipeline pair as mean $\pm$ std across subjects.

patterns (CSP) and covariance-based Riemannian geometry with tangent-space projection (TS). Pipeline definitions and hyperparameters follow the MOABB reference implementations to ensure comparability and reproducibility.

CSP-based pipelines. Common spatial patterns (CSP) compute supervised spatial filters that maximize the variance difference between the two MI classes, emphasizing class-discriminative components [52]. For each trial, the filtered signals are summarized by log-variance features, which are then classified. We evaluate CSP+LDA, a standard MI baseline using linear discriminant analysis, and CSP+SVM, using a linear support vector machine classifier [53]. CSP is the stage most directly affected by channel reduction because it learns spatial filters over the available electrodes. To keep the feature dimensionality commensurate with the montage size and to avoid over-parameterization on sparse layouts, we set the number of CSP components to the square root of the channel count, rounded to the nearest even integer; this preserves the MOABB reference choice of 8 components for the original 64-channel montage.

Riemannian-based pipelines. In these pipelines, each trial is represented by its channel covariance matrix, treated as a point on a curved Riemannian space. Covariances are then projected to a tangent space (TS) and vectorized, yielding Euclidean feature vectors that retain information about the underlying covariance geometry [54]. On this feature space, we evaluate TS+LR (logistic regression), TS+SVM, and TS+EL (logistic regression with elastic-net regularization) [55]. Compared to CSP, tangent-space methods often provide strong performance and robustness in MI benchmarks [50], and do not require electrode mask-specific tuning beyond the dimensionality change induced by the reduced number of channels.

C. Evaluation Protocols

We evaluate each pipeline-mask configuration under two complementary MOABB protocols, chosen to mirror two possible BCI-enabled IoS deployment scenarios. For binary MI classification, MOABB reports ROC-AUC as the primary metric, which we adopt for all main comparisons. ROC-

AUC measures class separability without fixing a specific decision threshold, quantifying how often trials from one class receive higher classifier scores than trials from the other. Because music-oriented BCI systems and related machine-learning studies may also require discrete-label performance, we additionally compute macro-F1 as a secondary descriptive metric. Macro-F1 is computed on the same data splits and protocols as ROC-AUC and differs only in the scoring function; ROC-AUC remains the primary outcome throughout the paper.

Performer-specific scenario. In networked musical performance ecosystems, a BCI can be treated as a calibrated sensing instrument. BCHJam, for example, places the BCMI on one or more musicians, whose brain signals are mapped to audio processing and mixed-reality visual effects for the audience [17]. This type of configuration assumes that the user is known in advance and can invest time in a setup or rehearsal phase to improve controllability. To model this scenario, we use MOABB’s within-session evaluation, where each subject is evaluated independently via 5-fold cross-validation within that subject’s session. The pipeline is thus trained and tested on data from the same participant, estimating how well a given electrode layout supports MI control after subject-specific calibration. We report mean $\pm$ std ROC-AUC across subjects, summarizing typical performance and inter-user variability in this calibrated setting.

Public-facing scenario. The same IoS logic also motivates audience-facing, installation-based, therapeutic, or educational settings in which BCI sensing may be exposed to subjects who are not known in advance. In these contexts, minimal setup is desirable and the decoder should generalize to unseen users. We model this scenario using MOABB’s cross-subject evaluation with a leave-one-subject-out (LOSO) scheme: at each iteration, the pipeline is trained on pooled data from all subjects except one and tested on the held-out subject. This estimates how reliably a given electrode layout supports subject-independent MI decoding without user-specific calibration. We report mean $\pm$ std ROC-AUC across held-out subjects. Since published MOABB baselines for Cho2017 primarily focus

on within-session results, cross-subject scores are presented here as an additional headset-aware generalization analysis, rather than as a replication target.

V. RESULTS

Before applying headset masks, we verified that the implementation reproduced MOABB’s reported within-session results for Cho2017 on the full 64-channel montage. Across the five reference pipelines, differences in mean ROC-AUC ranged from +0.08 to −1.37 percentage points, with standard deviations differing by less than 0.7 points. This replication check indicates that the MOABB configuration and evaluation protocol are aligned with the reference implementation before introducing electrode masking.

A. Performer-specific Simulation

Figure 4 reports performer-specific ROC-AUC (hereafter PS) for the 32 commercial headset masks and five pipelines. The full 64-channel montage is included only as a reference and is excluded from subsequent aggregate summaries. Macro-F1 follows the same relative ranking as ROC-AUC, but is systematically lower by approximately 3.6–4.2 percentage points on average across headsets, depending on the pipeline.

Using the best-pipeline score for each headset, caps and helmets achieve higher median ROC-AUC than headbands and headphones (72.24 and 69.33 vs. 58.71 and 59.02, respectively). Variability is also form-factor dependent: headbands show the largest inter-device spread (IQR = 10.42), indicating that sparse wearable layouts can differ substantially depending on electrode placement. Across form factors, TS-based pipelines most frequently reach the best ROC-AUC, with TS+EL and TS+LR dominating the top-ranked configurations.

TABLE II
CHANNEL COUNT-LEVEL SUMMARY.

N_{ch}	Headsets	Median Best ROC-AUC	Min	Max
≥ 21	3	73.77	72.24	75.43
15–20	4	73.27	72.60	74.12
9–14	4	69.78	66.70	70.31
8	6	69.51	63.26	70.88
7	3	66.82	62.93	68.88
5–6	4	63.99	56.95	67.12
4	3	57.18	57.03	60.24
1–3	5	56.85	53.91	64.12

Table II groups headsets by matched channel count where possible and by narrow channel-count ranges otherwise. For each group, we summarize the distribution of per-headset best-pipeline ROC-AUC across devices and report the median, minimum, and maximum scores.

B. Public-facing Simulation

We model the public-facing scenario (hereafter PF) with LOSO evaluation: each fold trains on a pooled set of 51 subjects and tests on one held-out, previously unseen subject. Figure 5 reports PF ROC-AUC across headset masks and pipelines, highlighting which layouts remain more stable under subject transfer.

		CSP+LDA	CSP+SVM	TS+SVM	TS+LR	TS+EL
Cap	Reference Cho2017 (64 ch)	70.56±15.05	70.55±14.94	74.70±13.66	74.71±13.70	75.38±14.55
	Emotiv Flex 2 (28 ch)	71.06±13.75	71.26±13.64	73.13±13.25	74.87±13.25	75.43±13.26
	BrainBit Dragon (21 ch)	69.04±12.77	69.03±12.71	69.78±12.94	71.95±13.29	72.24±13.20
	g.tec Unicorn Hybrid (8 ch)	68.78±12.36	68.76±12.26	69.08±12.35	70.13±12.28	70.21±12.24
	CGX Quick 32R (29 ch)	69.98±13.60	69.70±13.56	71.63±13.31	73.59±13.14	73.77±13.32
	A. B. M. B-Alert X24 (20 ch)	69.44±13.63	69.52±13.46	71.10±12.57	73.52±12.55	74.12±12.38
	CGX Quick 20R (19 ch)	69.22±13.39	69.31±13.20	70.72±12.56	72.37±12.99	72.60±12.85
	W. S. DSI-24 (19 ch)	69.52±13.48	69.60±13.40	71.07±12.57	73.33±12.73	73.81±12.61
	Ultracortex IV (16 ch)	68.85±13.40	68.83±13.40	70.50±11.80	72.41±12.52	72.72±12.54
	Emotiv Epoch X (14 ch)	62.42±12.17	62.27±12.26	65.42±12.02	66.70±12.41	66.43±12.67
Helmet	Bitbrain Diadem (12 ch)	65.30±11.70	65.17±11.45	67.89±11.01	69.09±11.28	69.33±11.51
	A. B. M. B-Alert X10 (9 ch)	69.02±12.42	69.03±12.41	69.75±12.46	70.15±12.78	70.31±13.00
	Bitbrain Hero (9 ch)	68.01±14.61	67.92±14.63	69.29±13.42	70.23±13.57	70.09±13.54
	Bitbrain Air (8 ch)	61.75±10.07	61.44±10.30	62.71±10.83	63.26±10.90	63.13±11.32
	Neurosky Crown (8 ch)	68.57±11.96	68.55±12.12	70.41±12.17	70.88±12.34	70.83±12.28
	Ultracortex IV (8 ch)	67.74±11.74	67.78±11.68	69.12±11.52	69.71±11.46	69.99±11.43
	W. S. DSI-7 (7 ch)	67.88±13.56	67.56±13.63	68.35±13.56	68.83±13.89	68.88±13.83
	W. S. DSI VR300 (7 ch)	65.48±11.70	65.40±11.74	66.28±11.53	66.70±11.79	66.82±11.87
	W. S. DSI VRVEP (7 ch)	61.40±9.73	61.59±9.79	62.33±9.25	62.93±9.66	62.81±9.71
	Mindrove Arc (6 ch)	63.82±12.45	63.48±12.66	66.67±13.48	66.82±13.54	66.77±13.65
Headband	Emotiv Insight (5 ch)	57.91±9.26	57.57±9.36	61.12±10.03	61.16±9.95	60.86±10.20
	Muse 2 Headband (2 ch)	55.50±8.11	55.07±8.27	56.50±10.38	56.85±10.24	56.62±10.58
	Neurosky Mindwave 2 (1 ch)	53.91±6.01	53.91±6.01	53.91±6.01	53.87±6.02	53.66±5.89
	BrainBit Headband Pro (8 ch)	64.07±10.94	64.00±10.89	68.14±11.72	68.34±11.87	68.29±11.76
	Mindrove Vision (8 ch)	66.44±11.11	66.32±11.20	68.23±11.97	68.97±11.76	69.03±11.95
	Mindrove Lucid (6 ch)	62.16±9.45	62.05±9.44	66.81±10.97	67.09±10.85	67.12±10.73
	Bitbrain Iron (5 ch)	54.67±8.74	54.46±8.67	56.21±12.10	56.63±12.14	56.95±11.86
	BrainBit Headband (4 ch)	56.54±8.93	56.39±8.80	56.85±8.80	56.88±8.91	57.03±8.80
	Mindrove Bright (4 ch)	57.90±8.65	57.81±8.63	59.67±9.91	60.24±9.69	60.23±9.81
	Neuro SenseBand (4 ch)	55.17±8.12	55.29±7.93	56.99±10.11	57.18±10.07	57.02±9.98
Headphones	Muse S Athens (2 ch)	55.50±8.11	55.07±8.27	56.50±10.38	56.85±10.24	56.62±10.58
	BrainBit Headphones (3 ch)	62.14±11.12	61.98±11.14	63.82±11.94	64.12±11.78	63.95±11.82
	Emotiv MN8 (2 ch)	53.77±6.65	53.50±6.53	53.89±7.02	53.91±7.11	53.69±7.15

Fig. 4. Performer-specific (PS) ROC-AUC averaged across 52 subjects for 32 virtual headset masks and five pipelines. Headsets are grouped by form factor and ordered by matched channel count; each cell reports the subject-level mean and standard deviation under 5-fold within-session cross-validation.

As expected, performance decreases relative to performer-specific (PS) evaluation, reflecting the challenge of generalizing MI decoding across users. To complement the heatmap, Table III aggregates results across the 32 commercial layouts, excluding the 64-channel reference, and summarizes the PS-to-PF change at pipeline level. Averaged across layouts, TS-based pipelines remain slightly higher in PF ROC-AUC than CSP-based pipelines, but show larger generalization drops.

TABLE III
PIPELINE-LEVEL SUMMARY AVERAGED ACROSS DEVICES, WITH $\Delta = \text{PF} - \text{PS}$ IN PERCENTAGE POINTS (PP).

	CSP+LDA	CSP+SVM	TS+SVM	TS+LR	TS+EL
PS	63.53±11.05	63.43±11.04	65.12±11.37	65.92±11.47	65.98±11.51
PF	60.63±9.81	60.61±9.84	61.38±9.96	61.27±9.95	61.40±9.97
Δ (pp)	−2.90	−2.82	−3.74	−4.65	−4.58

The generalization gap is not uniform across layouts. When computed as the difference between the best PF and best PS ROC-AUC for each headset, the median drop is larger for caps and helmets (−5.74 and −5.14 pp) than for headbands

		CSP+LDA	CSP+SVM	TS+SVM	TS+LR	TS+EL
Cap	Reference Choz2017 (64 ch)	66.25±12.64	66.43±12.60	66.34±11.26	67.02±11.31	67.46±11.41
	Emotiv Flex 2 (28 ch)	66.07±13.08	66.18±13.14	67.30±11.82	67.65±11.84	67.78±11.88
	BrainBit Dragon (21 ch)	66.08±13.08	66.11±13.04	66.20±11.78	66.43±11.65	66.50±11.69
	g.tec Unicorn Hybrid (18 ch)	64.72±12.04	64.76±12.03	64.42±11.72	64.26±11.50	64.29±11.52
	CGX Quick 32R (29 ch)	66.14±13.41	66.01±13.52	66.11±11.22	66.55±11.25	66.71±11.28
	A. B. M. B-Alert X24 (20 ch)	65.73±12.76	65.78±12.73	66.23±11.73	66.28±11.64	66.36±11.65
	CGX Quick 20R (19 ch)	65.81±12.78	65.89±12.75	66.07±12.05	66.45±11.82	66.52±11.84
	W. S. DSI-24 (19 ch)	65.81±12.78	65.89±12.75	66.07±12.05	66.45±11.82	66.52±11.84
	Ultracortex IV (16 ch)	64.58±12.37	64.70±12.40	65.43±12.31	65.69±12.29	65.76±12.29
	Emotiv Epoch X (14 ch)	57.64±9.28	57.30±9.40	60.84±8.86	60.70±8.91	60.76±8.92
Headset	Bitbrain Diadem (12 ch)	61.80±11.20	61.78±11.21	62.70±10.43	62.70±10.47	62.70±10.49
	A. B. M. B-Alert X10 (10 ch)	66.11±13.06	66.16±13.11	65.61±12.32	65.61±12.28	65.62±12.30
	Bitbrain Hero (9 ch)	65.97±12.67	66.20±12.89	67.04±12.66	66.98±12.71	66.98±12.72
	Bitbrain Air (8 ch)	53.68±7.48	53.79±7.75	56.34±6.45	56.29±6.54	56.28±6.57
	Neurocity Crown (8 ch)	64.57±11.81	64.60±11.81	65.74±12.60	65.71±12.61	65.70±12.60
	Ultracortex IV (8 ch)	61.91±9.89	61.76±9.88	62.82±12.26	62.73±12.14	62.73±12.16
	W. S. DSI-7 (7 ch)	66.10±13.44	66.18±13.41	65.56±12.68	65.48±12.62	65.49±12.61
	W. S. DSI-VR300 (7 ch)	62.33±10.82	62.03±10.89	62.10±10.55	62.20±10.54	62.21±10.54
	W. S. DSI-VRVEP (6 ch)	57.81±8.47	57.79±8.45	58.60±8.22	58.75±8.19	58.78±8.20
	Mindrove Arc (6 ch)	61.58±10.63	61.51±10.59	64.70±12.07	64.74±11.99	64.74±11.99
Headband	Emotiv Insight (5 ch)	57.08±7.24	56.95±6.94	58.04±6.95	58.06±7.05	58.06±7.06
	Muse 2 Headband (5 ch)	55.07±6.19	55.04±6.46	54.46±6.24	55.21±6.74	55.21±6.73
	Neurosky Mindwave 2 (4 ch)	52.93±6.19	52.93±6.19	52.93±6.19	52.93±6.19	52.93±6.19
	BrainBit Headband Pro (8 ch)	61.91±9.89	61.76±9.88	62.82±12.26	62.73±12.14	62.73±12.16
	Mindrove Vision (8 ch)	60.33±8.76	60.19±9.05	62.94±11.24	62.88±11.23	62.90±11.23
	Mindrove Lucid (6 ch)	60.38±7.87	60.36±7.79	61.02±11.34	60.86±11.45	60.89±11.46
	Bitbrain Ikon (5 ch)	53.71±6.17	53.75±6.14	53.86±5.90	54.16±5.84	54.18±5.85
	BrainBit Headband (4 ch)	53.70±6.29	53.73±6.31	53.72±7.78	53.63±7.71	53.63±7.69
	Mindrove Bright (4 ch)	54.03±7.04	54.13±7.02	54.49±7.47	54.58±7.34	54.58±7.36
	Neuro SenseBand (4 ch)	55.75±5.91	55.75±5.98	55.46±6.23	55.43±6.31	55.44±6.29
Headphones	Muse S Athena (2 ch)	55.07±6.19	55.04±6.46	54.46±6.24	55.21±6.74	55.21±6.73
	BrainBit Headphones (3 ch)	61.27±10.20	61.24±10.23	62.26±11.86	62.20±11.79	62.19±11.79
	Emotiv MN8 (2 ch)	54.40±4.85	54.20±4.61	54.41±4.94	54.57±5.31	54.56±5.31

Fig. 5. Public-facing (PF) ROC-AUC averaged across 52 held-out subjects for 32 virtual headset masks and five pipelines. Each cell reports the subject-level mean and standard deviation under LOSO evaluation.

and headphones (-4.41 and -0.60 pp). The smaller drop observed for sparse layouts should not be interpreted as greater generalization robustness, since many already perform close to chance in the PS setting and are therefore subject to a floor effect, leaving limited room for further degradation. A similar pattern appears across channel-count groups: masks with 15 or more matched channels show median drops around -7 pp, whereas masks with one to three matched channels show a much smaller median change (-1.64 pp).

C. Summary

A within-manufacturer comparison further illustrates performance differences among layouts at fixed matched channel count. *Wearable Sensing* offers three headsets (*DSI-7*, *DSI-VR300*, and *DSI-VRVEP*) that share the same number of electrodes ($N_{\text{ch}} = 7$), yet implement distinct layouts. *DSI-7* includes central electrodes and adjacent frontal and parietal sites relevant to MI decoding and achieves higher performer-specific performance (best ROC-AUC 68.88 ± 13.83) than *DSI-VR300* (best 66.82 ± 11.87) and *DSI-VRVEP* (best 62.93 ± 9.66), whose layouts are shifted toward parieto-occipital cov-

erage, more typical of visually oriented paradigms. More broadly, this example shows that low-density headsets can remain competitive when electrode placement targets informative regions: despite using only 7 channels, *DSI-7* remains within about 5 ROC-AUC points of *DSI-24* ($N_{\text{ch}} = 19$; 68.88 ± 13.83 vs. 73.81 ± 12.61).

Figure 6 provides the overall synthesis of the benchmark. Because market prices vary substantially across regions and over time, cost is reported only qualitatively. Marker area is therefore proportional to a four-level logarithmic cost tier, while square markers denote layouts for which no reliable online price estimate was available. For each headset layout, it plots the best performer-specific ROC-AUC against matched channel count and connects it to the corresponding best public-facing ROC-AUC. The resulting arrows visualize the trade-off between calibrated performance and subject-transfer robustness, showing that denser layouts generally reach higher performer-specific scores but often undergo larger degradation under public-facing evaluation, whereas sparse layouts tend to cluster at lower absolute performance with smaller drops. Together, these patterns suggest that headset layouts should be screened not only by channel density, but also by their overlap with MI-relevant sensorimotor regions.

VI. DISCUSSION

The reported scores characterize MI decoding performance associated with electrode topology and channel availability under controlled spatial subsampling, using a single public dataset and a specific binary MI task, namely left- vs. right-hand imagery. They do not estimate the physical performance of the commercial headsets themselves. Absolute performance and variability may differ with other MI datasets, task designs, trial counts, session structures, participant populations, and real-device acquisition factors such as electrode technology, amplifier characteristics, proprietary preprocessing, wireless stability, motion artifacts, and electrode-skin coupling. Accordingly, the benchmark should be read as an interpretable baseline for topology-driven constraints and preliminary screening of wearable EEG headsets.

Moreover, in BCI-enabled IoS design, a wearable EEG headset is also a sensing node in a networked sound-interaction system. Figure 6 reports the topology-performance side of this problem, while Table I summarizes deployment-oriented attributes such as form factor, extra sensors, connectivity model, raw/API access, and battery class. Taken together, these two views may support early-stage headset screening: the benchmark indicates whether a layout plausibly samples MI-relevant scalp regions, while the headset collection indicates whether the same device profile is practically compatible with IoS constraints such as wireless communication, real-time data access, multimodal sensing, and autonomy.

A. Deployment Attributes Beyond Topology

Real-time musical or sound-based interaction depends on access to usable data streams through SDKs, APIs, or raw EEG streams; art installations and therapeutic sessions may

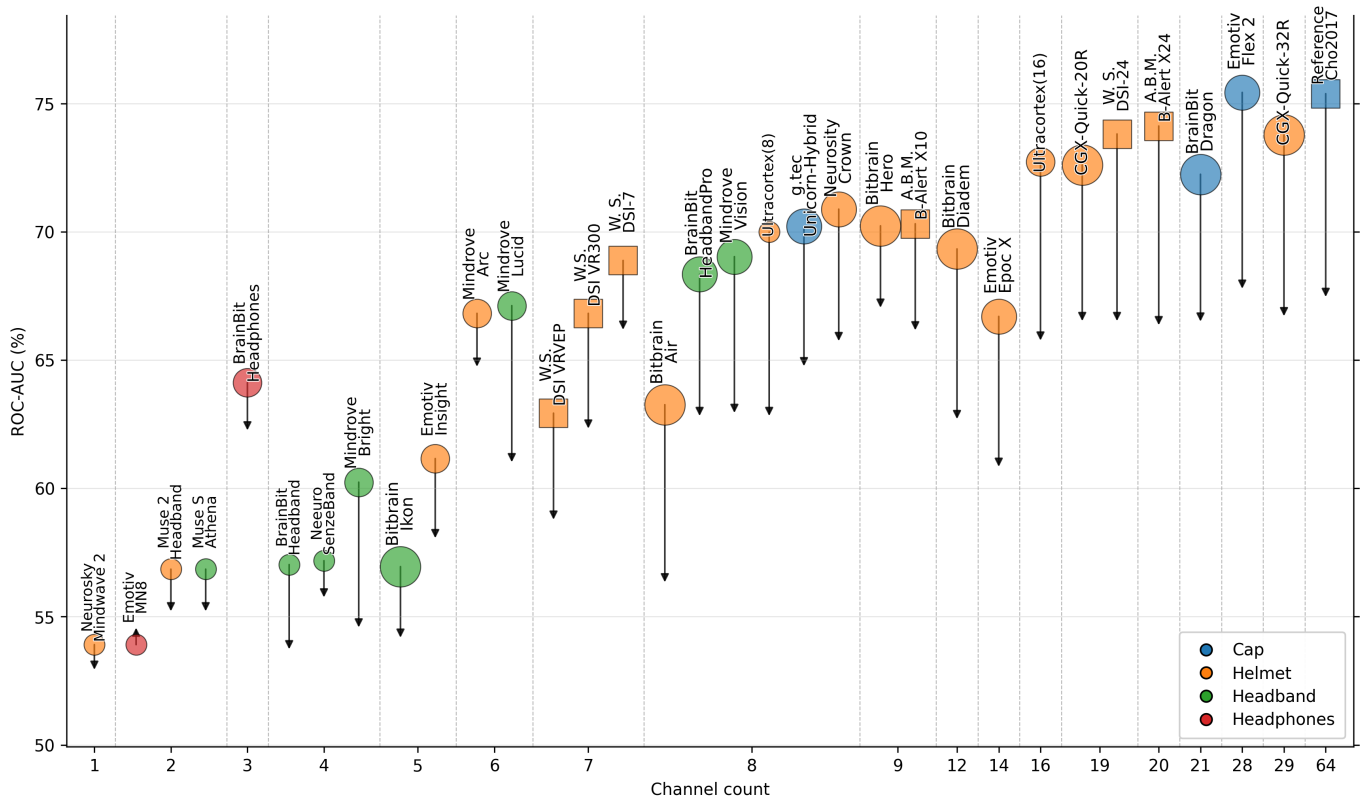


Fig. 6. Topology–performance trade-off across commercial EEG layouts. Markers show best performer-specific ROC-AUC versus matched channel count; black arrows indicate the change to public-facing performance (best pipeline per protocol). Color encodes form factor, while marker size encodes qualitative cost tier, with larger markers indicating higher cost. Square markers denote layouts for which no reliable online price estimate was available.

prioritize fast setup, wireless operation, and sufficient battery life; and multimodal IoS scenarios may benefit from inertial, physiological, audio, or auxiliary electrophysiological sensors integrated into the same wearable platform.

In the current headset collection (Table I), the catalogue is dominated by non-cap devices: 19 helmets, 8 headbands, 3 caps, and 2 headphones. This suggests a commercial design tendency toward faster donning and wearability rather than laboratory-style cap coverage. The Raw/API access model is also uneven: 18 out of 32 devices are marked as providing a free/open Raw/API pathway, while 5 require paid access, 5 follow a mixed access model, and 4 remain unclear or not publicly verified. Battery information is available for 27 devices: 12 are reported in the ≤ 6 h class, 10 in the 6–12 h class, and 5 in the >12 h class.

Electrode technology introduces an additional deployment trade-off: 21 devices use dry technologies, 5 use semi-dry electrodes, while 6 rely on wet or saline sensing. Dry systems eliminate gel preparation and cleaning, supporting faster donning and repeated or public-facing use, but contact quality can be more sensitive to fit, hair, motion, and electrode–skin coupling. Wet gel or saline electrodes generally provide more stable contact, at the cost of additional preparation, consumables, and cleaning [44], while semi-dry solutions offer an intermediate compromise but may be affected by electrolyte

drying over time.

Connectivity further differentiates candidate IoS sensing nodes. Thirty devices report an explicit wireless connection: 26 include a Bluetooth-family link (BT, BLE, or both), while the 4 MindRove devices rely on Wi-Fi Direct; the 2 OpenBCI configurations are board-dependent. At least five devices also report USB or USB-C as a wired or charging/data option. Connectivity diversity entails different assumptions about latency, local-network integration, bandwidth, setup complexity, and robustness in shared performance or installation environments.

Finally, 27 devices report at least one additional sensor or auxiliary channel. Inertial measurement units are the most common extension, typically accelerometers, appearing in 25 devices. Auxiliary biosignal channels (ExG) appear in 7 devices, photoplethysmography (PPG) in 3, microphones in 2, and functional near-infrared spectroscopy (fNIRS) in 1. Notably, *DSI-VR300* also provides explicit VR-headset compatibility through an adaptor kit, making it relevant for IoS scenarios involving mixed-reality or virtual-reality interaction.

B. Low-density Layouts and System-Level Efficiency

When electrode placement remains compatible with task-relevant sensorimotor activity, reducing the number of channels can also improve system-level efficiency in IoS settings. For an uncompressed EEG stream, the nominal data rate scales

with the number of channels, sampling frequency, and bit depth. Fewer channels can therefore reduce the required wireless bandwidth and the amount of data that must coexist with audio, inertial, physiological, and network-control streams.

A lower channel count can also reduce computational requirements by decreasing the dimensionality of preprocessing, feature extraction, and classifier input, which may be relevant for battery-powered, mobile, or embedded sensing nodes. From this perspective, the design goal is not necessarily to maximize accuracy, but to identify the layout that preserves sufficient task-relevant coverage for the intended control regime.

C. Scenario-dependent Constraints

The performer-specific (PS) and public-facing (PF) protocols correspond to different IoS design assumptions. In PS settings, the BCI user is known and calibration or rehearsal can support more demanding mappings between MI output and musical parameters. In PF settings, users may interact briefly and without prior calibration; therefore, robustness to unseen users becomes as important as the best calibrated score. The non-uniform PS-to-PF drops in Figure 6 show that similar channel counts can lead to different generalization profiles, reinforcing the need to consider topology together with the intended control regime.

This distinction also affects interaction design. PS systems may exploit tighter mappings and higher-resolution control strategies, whereas PF systems should favour more forgiving mechanisms, such as conservative triggering, gradual evidence accumulation, adaptive thresholds, or fallback interaction modes. Headset selection should therefore be understood as a joint decision between electrode topology, deployment constraints, and the expected calibration regime.

VII. CONCLUSION AND FUTURE WORK

This work asked a practical design question: *how do MI decoding performance and variability change when moving from laboratory caps to commercial wearable headsets with low-density layouts?*

We propose a device-aware topology benchmark over 32 commercial wearable EEG headsets, represented as electrode masks on a 64-channel MI reference dataset. The benchmark varies commercial electrode masks while keeping the dataset, preprocessing framework, pipeline families, and evaluation protocols fixed. The results quantify how current commercial wearable EEG topologies translate into MI decoding performance. Layouts with comparable channel counts show different decoding performance, with the strongest results generally observed for masks that sample central sensorimotor regions. The shift from performer-specific to public-facing evaluation further shows that headset suitability depends not only on calibrated performance, but also on how much of that performance is preserved for unseen users.

The headset collection further shows that topology is only one part of the IoS design challenge. The benchmark identifies which layouts plausibly support MI-based control, while the

deployment attributes indicate which headset profiles may function as practical sensing nodes in networked musical and sound-based scenarios. The proposed analysis should therefore be interpreted as an early-stage screening tool rather than as a ranking of physical products.

The analysis is based on virtual channel masks derived from a single public dataset and a binary left- vs. right-hand MI task; it does not capture device-specific factors such as electrode technology, amplifier characteristics, fit stability, wireless robustness, latency, motion artifacts, or proprietary preprocessing. Future work should compare commercial layouts against random channel-count-matched subsets, validate the observed topology-based trends with recordings from selected commercial headsets, extend the analysis to additional MI datasets and multi-session protocols, and model signal-quality variability across dry, semi-dry, wet, and gel-based sensing technologies. The same headset collection and methodology could also be extended to other BCI paradigms relevant to musical interaction, including SSVEP, P300, ASSR, auditory imagery, and hybrid multimodal paradigms. Finally, future work should assess the robustness of the observed layout-dependent performance trends across a broader range of decoding approaches, including deep-learning architectures.

To support replication and extension, a companion repository is released with per-subject results in CSV format and Python code implementing the headset collection and benchmark scripts [47].

ACKNOWLEDGMENT

Giuseppe Bergamino's PhD scholarship is funded by the Marche Region within the framework of the "Innovative PhD Programmes", under the Regional Programme of the European Social Fund Plus (PR FSE+) 2021–2027.

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